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A novel medical image fusion approach based on fractional wavelets transform

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Abstract. Multi-modal image fusion is a process of integrating complementary information from multiple images of different scene. A novel medical image fusion algorithm based on the fractional wavelets transform (FRWT) is proposed in this paper. The method is implemented to fractional wavelets transform to get highpass and lowpass wavelets coefficients. Then according to the different frequency fusion rules combine the coefficients to obtain the fused image. The performance of the proposed fusion method is assessed by experiment, and the results indicate the proposed method outperforms the traditional approaches.

1. Introduction

Recent years, image fusion has become an important technique for various image processing and computer vision application such as target recognition, remote sensing, night vision, and medical diagnosis [1]. Due to different tomography theories, several of medical image modalities are developed. Commonly the medical image separates two varieties: One is anatomical medical image, like CT, MRI and so on. Another is functional medical image such as PET. Multi-modal medical image fusion, an easy access for physicians to understand the lesion by reading images of different modalities, has been emerging as a new and promising research area due to the increasing demands in clinical applications. For example, combined MRI/CT imaging can concurrently visualize anatomical and physiological characteristics of human body for diagnosis and treatment planning [2]. In oncology, the combined PET/CT imaging is helpful to view the tumor activity, allowing physicians to better understanding the effects of cancer treatment [3].

The wavelets transform have emerged as a powerful tool in image fusion, and the advantage of wavelets transform is that it can be analyze signal in time domain and frequency domain, respectively. Since Mendlovic and Zalevsky proposed the fractional wavelets transform (FRWT) in 1997[4], the FRWT become a new time frequency analysis method in signal analysis and process. It combines the fractional Fourier transform (FRFT) and the wavelets transform merits, so it has multi-resolution and fractional domain analysis characteristics.

In this paper, a novel approach based on FRWT is proposed, which gives the simulation results and the performance evaluation. The paper is organized as follows. In section 2 the fractional wavelets transform algorithm is introduced. The image fusion framework based on FRWT is presented in section 3. In section 4 the performance of the proposed fusion method is evaluated via experiments. Finally, the conclusion follows.

2. Fractional wavelets transform

The continuous wavelets transform (CWT) is defined as the sum over all time of the signal multiple by scale, shifted version of the wavelets function [5]. For a given scaling parameter, the wavelets is translated by varying the parameter b. The wavelets transform function is defined as

$$w(a,b)=\int_t f(t)\frac{1}{\sqrt{|a|}}\psi((t-b)/a) \tag{1}$$

Where b is location parameter, a is scaling parameter.

Multiplying each coefficient by the appropriately scaled and shifted wavelets yields the constituent wavelets of the original signal. Via the wavelets equation, for every (a,b), the transform result is that obtain a wavelets coefficient, representing how much the scaled wavelets is similar to the function at location, $t = b/a$.

Based on the basic wavelets transform function, the fractional wavelets transform have been developed. The fractional wavelets transform is formulated as:

$$\left(T^{ave} f\right)(\alpha,a,b) = |a|^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(t) e^{i\frac{t^2-b^2}{2}\cot\alpha} \bar{\varphi}(\frac{t-b}{a})dt \tag{2}$$

Where $\alpha=p\pi/2$, p is the fractional level of the sub-image.

The two-dimensional FRWT can be formulated as follows:

$$w(a_{mn},\tilde{b}) = \iiiint B_{p1,p2}(x,y;x',y') f(x,y)\times h_{a_{mn}b}^{*}(x',y')dxdydx'dy' \tag{3}$$

Where $h_{a_{mn}b}^{*}(x',y')$ is the mother wavelets function, $B_{p1,p2}(x,y;x',y')$ is the kernel of the transformation and equals.

The fractional wavelets transform restructure formula is as follows:

$$f(x,y) = \frac{1}{c}\iint F[\sum_m \sum_n \iint \frac{1}{a_m a_n} w(a_{mn},\tilde{b}) h(a_m u, a_n v)\exp(-j2\pi u b_{x'}, -j2\pi b_{y'}) db_{x'} db_{y'}] \times(x',y') B_{-p_1,-p_2}(x,y;x',y')dx'dy' \tag{4}$$

Due to the characteristic of FRWT, the image information can be reflect in the time domain and frequency domain simultaneously. The fractional variable p improves the FRWT flexibility which suits analyzing non-steady signal and capturing more information of the image.

3. Medical image fusion

The Fig.1 shows the proposed general image fusion framework in wavelets domain. The image fusion scheme based on fractional wavelets transform (FRWT) can be described as follows:

Step 1: FRWT decomposition

Decomposing source image into low frequency components, horizontal, vertical and diagonal high frequency components via wavelets transform respectively, then fusing low frequency and high frequency coefficients with different fusion rules respectively.

Step 2: Lowpass frequency subbands fusion

In order to obtain more information, low frequency coefficients of the fused image are replaced according to the regional energy maximum value in proposed algorithm.

Let E_l denote the region energy by the $M\times N$ sliding widow which located at (i,j). And the $C^l(i,j)$ denote the lowpass coefficients located at (i,j). The fusion rule can be described as:

If $mat^l \le Thr$, the fused lowpass coefficients:

$$F^l(i.j) = \begin{cases} C_A^l(i,j), & E_A^l(i,j) \ge E_B^l(i,j) \\ C_B^l(i,j), & E_B^l(i,j) < E_A^l(i,j) \end{cases} \tag{5}$$

If $mat^l > Thr$, the fused lowpass coefficients:

$$F^l = \frac{M_A^l(i,j)+M_B^l(i,j)}{2} \tag{6}$$

Where mat^l is the matching degree of the region energy of the input images. Thr denotes the threshold of the image matching degree. And M^l indicates the region average value.

Step 3: Highpass frequency subbands fusion

The highpass subbands coefficients are the representation of edge information of an image. Therefore, the fusion rule of highpass frequency subbands is based on the maximization of the variance value, that is

$$C_F^l(i,j)=\begin{cases} D_A^l(i,j), & V_A^l(i,j)>V_B^l(i,j) \\ D_B^l(i,j), & V_A^l(i,j)\le V_B^l(i,j) \end{cases} \tag{7}$$

Where the $V^l(i,j)$ is the variance of the $M\times N$ sliding widow of the highpass frequency coefficients. $D^{\bar{l}}(i,j)$ denotes the average of the area $M\times N$ of the highpass coefficients.

Step 4: IFRWT reconstruction

Obtaining the fused image through inverse fractional wavelets transform.

4. Experiment results and analysis

4.1 Evaluation criteria

Three evaluation criteria we used

Entropy reflects the amount of information carried by image, bigger entropy means better fusion effect and stronger detail expression performance. It can be described as:

$$E=-\sum_{i=0}^{L-1} p(i)\log p(i) \tag{8}$$

Average gradient is used to indicate the detail of the image, the greater the AG is, and the clearer is the image.

$$Q_{\overline{AG}}=\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\sqrt{(\frac{\partial}{\partial m}I)^2+(\frac{\partial}{\partial n}I)^2} \tag{9}$$

Figure definition reveals the image definition.

$$Q_d=\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\sqrt{\frac{(f(i,j)-f(i,j+1))^2+(f(i,j)-f(i+1,j))^2}{2}} \tag{10}$$

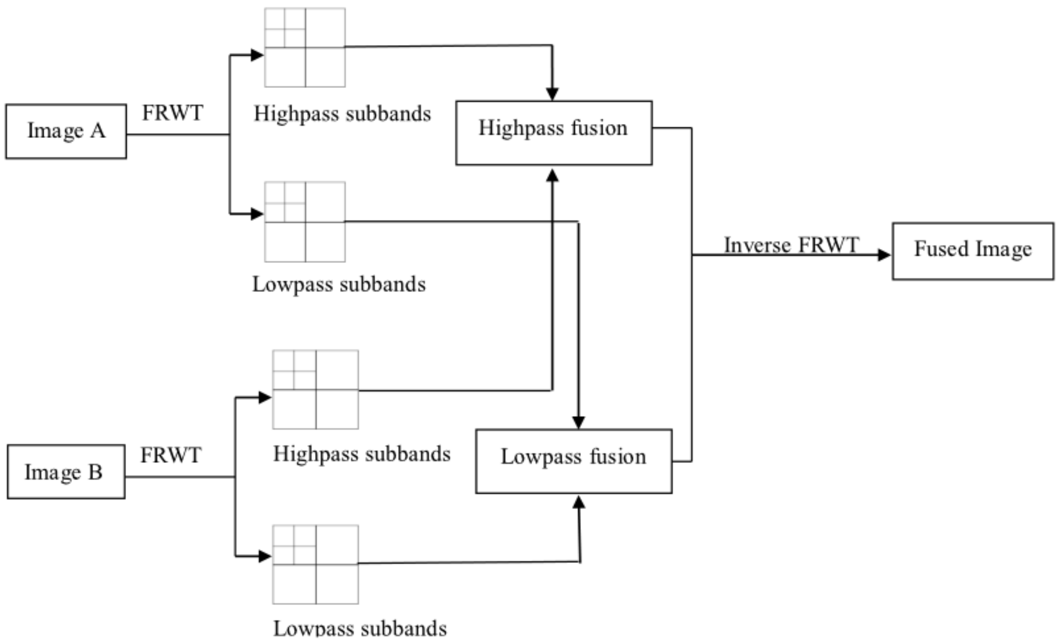

Fig. 1 Multi-modal image fusion framework based on FRWT

4.2 Experiment result and analysis

We now test the performance of the proposed FRWT based medical image fusion algorithm. To evaluate the performance of the method, two experiments have been implemented. The images used can be downloaded from the web site (http://med.harvard.edu/AANLIB/home.html). We choose db4 wavelets base. And the decomposed level is 3. According to experiments, the optimal region of fractional coefficient p is $[0.3, 0.7]$. In this paper, the choice of p is 0.5.

The first experiment result of the CT/MRI fusion is shown in figure (a1)-(b4). The a1, a2 represent the performance based on different transform method, and b1-b4 represent the performance based on different fusion method. We used pixel maximum, pixel average and pixel threshold as fusion rule-1, rule-2 and rule-3 to contrast with proposed approach which is fusion rule-4.

The second experiment result of the MRI/SPET fusion is shown in figure (c1)-(d4). In the figure, c1 and c2 is the fusion result based on DWT and FRWT transform algorithm. The d1-d4 is the fusion result based on different fusion method.

Following table demonstrates the various quality measure for different image fusion algorithm. the proposed algorithm is effectively completed multi input images fusion. Via the evaluation criteria, the performance of the proposed method is shown in table 1 and table 2, which significantly outperform the wavelets transform based method.

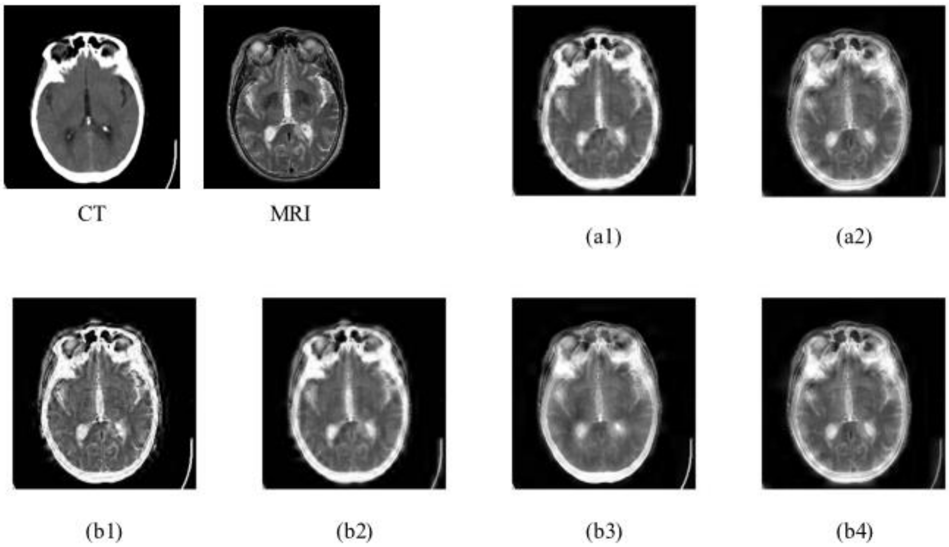

Figure 2. CT/MRI fusion result

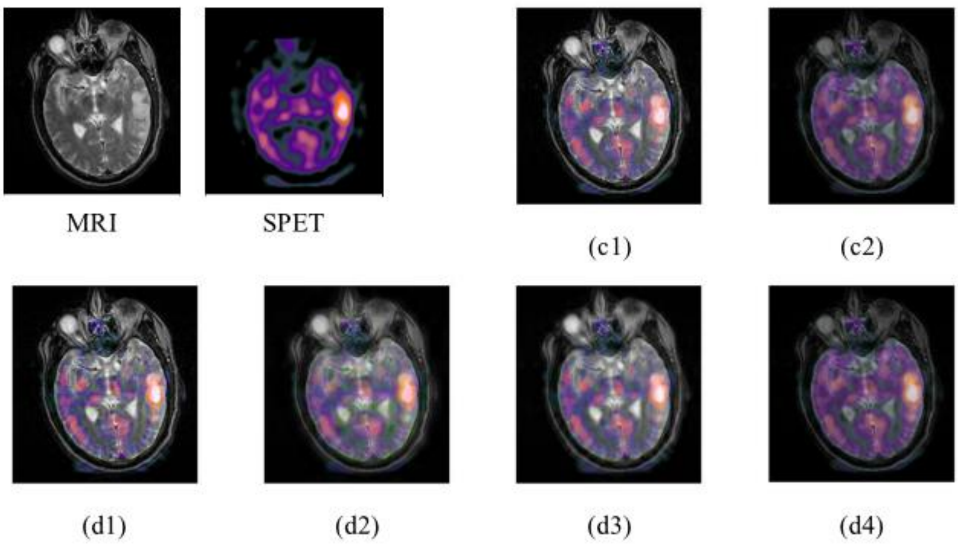

Figure 3. SPECT/MRI fusion result

Table 1. Performance of different transform method for CT/MR and SPET/MRI

	Transform method	Entropy	Qav	Qd
CT/MRI Fusion	WT based method	3.8650	4.9231	3.2051
	FRWT based method	4.1752	4.7052	5.9210
SPET/MRI Fusion	WT based method	3.7823	5.2005	5.3245
	FRWT based method	3.8305	4.9050	5.7782

Table 2. Performance of different fusion rules for CT/MRI and SPET/MRI

	Fusion rules	Entropy	Qav	Qd
CT/MRI Fusion	Rule-1	3.3260	5.1965	5.8759
	Rule-2	3.5039	3.8870	4.2005
	Rule-3	3.7728	3.6416	4.0050
	Rule-4	3.8305	4.9050	5.7782
SPET/MRI Fusion	Rule-1	3.7580	4.8281	5.6921
	Rule-2	3.9636	3.2856	3.6757
	Rule-3	3.9201	3.4394	3.8174
	Rule-4	4.1752	4.7052	5.9210

5. Summary

A novel medical image fusion algorithm based on fractional wavelets transform is proposed in this paper. In the proposed method, the multi-modal source image is represented in the fractional wavelets transform domain. The different fusion rules are applied to the highpass and the lowpass coefficients. Experiments show that the proposed can well complete multi-modal meidcal image fusion. How to improve the complexities of time is important issue can be further researched.

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